2013

Applying Alternative Decision-making Approaches to a Complex Supplier Selection Problem

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Keywords
Decision-making, systems engineering, trade studies, supplier selection

Disciplines
Systems Engineering

Comments
This proceeding is published as Componation, Paul J., Michael C. Dorneich, Guiping Hu, and Gillian M. Nicholls. "Applying Alternative Decision-making Approaches to a Complex Supplier Selection Problem." In *Proceedings of the 2013 IIE Annual Conference and Expo*. Institute of Industrial Engineers (IIE). Pages 1139-1147. May 18-22, 2013, San Juan, Puerto Rico. Posted with permission.

Proceedings of the 2013 Industrial and Systems Engineering Research Conference
A. Krishnamurthy and W.K.V. Chan, eds.

Applying Alternative Decision-making Approaches to a Complex Supplier Selection Problem

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Abstract

Prior work has been completed on understanding how an organization's decision-making approach can influence the selection of alternative vendors when setting up a supply chain system. Teams using different decision-making approaches on identical performance data did end with different vendor recommendations. One possible explanation of this result was that the data set on vendor performance was limited to five vendors and four variables; however the decision-making approaches had significantly different cognitive requirements. The team members preferred cognitively simple approaches such as Weighted Sum and to a lesser degree SMART with this relatively limited data set. The more cognitively complex approaches, TOPIS, AHP, and ELECTRE, had lower preference levels. This paper reports on an extension to the original work where team members utilized the same set of five decision-making approaches, but applied them to a more complex vendor selection problem. Results indicate that the vendor selection recommendations had less variability than the previous study, team members appeared more comfortable with their results, and better able to explain their work to managers when approaches that were more cognitively complex were used. The team members did report some time issues completing their work with some decision-making approaches.

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1. Introduction
Systems engineers commonly conduct trade studies to support system development, but conducting a sound trade study is still both a science and an art. The science of a trade study is obtaining data, analyzing the data, and reaching a sound, justifiable prioritization of the alternatives. The art is to know which tools to use, how to deal with decision makers, and knowing what criteria are the critical drivers to focus upon. A significant amount of work has been done to explore the science of trade studies. Less has been to done to understand the art. This paper adds to the understanding of the art by extending prior work on how decision makers perceive different trade study approaches when they are faced with a vendor selection problem in setting up a new supply chain. Two factors were explored: the decision-making approaches and the complexity of the data set. Teams were all trained in a range of decision making approaches, and then each team was assigned one of the approaches to solve a specific vendor selection problem. Although the approaches were all generally applicable to solving the specific problem there were notable differences in the teams' assessments of the ease of use and applicability. This study looked specifically at how different sized of data sets on vendors influenced how the teams perceived different decision-making approaches.

In decision-making the relative worth of individual alternatives can be evaluated by looking at the performance of each alternative relative to a set of desirable criteria, and then combining the scores to determine an alternative's overall performance. Weighting of the criteria and the techniques used to combine the scores vary to reflect the decision maker's preferences. Two of the most widely cited references on trade studies are Keeney and Raiffa's work on determining utilities for criteria when the criteria can be viewed as independent of each other [1], and Edwards' work on determining quantitative values based upon subjective inputs from decision makers [2]. There has also been significant work examining the effect that decision makers' biases have on the trade study process. Examples of these works include studies on how decision makers can be overly influenced by the initial data [3], how judgments may be intransitive [4] and how emotions can influence decisions [5].

More recent work in decision-making has included attempts to better define the science, or the process, of conducting the study. A commonly used reference is the International Council on Systems Engineering (INCOSE) Systems Engineering Manual [6] which outlines the basics of the systems engineering decision-making [trade study] process. Another source is the National Aeronautics and Space Administration (NASA) Systems Engineering Handbook [7]. These and other resources provide guidance on how to conduct a study. However, details on the specific methods to use are minimal. Even if the trade study process is followed, there are still numerous points where difficulties can surface, such as reaching consensus on the approach used, determining the appropriate criteria, and determining how to evaluate alternatives [8].

Selecting an appropriate approach is not a trivial task. One significant effort presented by Guitouni and Martel provided a set of guidance to help the decision maker select an appropriate tool [9]. Care must be taken to select an approach that is appropriate to the decision making situation and not to select a tool based on odd mathematical vagary of a combining function [10]. Some interesting work has also been reported looking at the results of different tool use applied to the same data set. An analysis using different Multi-Attribute Decision-Making (MADM) techniques showed that different results may be achieved in analyzing wireless networks when Simple Additive Weighting (SAW), Weighted Product (WP) [11] and Technique for Order Preference by Similarity to Ideal Solution (TOPIS) [12] were used [13]. A second work examining vendor selection issues and how MADM tools such as ELECTRA and an outranking approach can be used [14]. This second work is of particular interest because of the increased attention paid to designing and managing efficient and effective supply chains in both industry and government applications. In this paper we are reporting on a continued extension to the supply chain problem. Here we looked at how the size of the data based used influenced the team perceived the specific decision-making approach they were using.

2. Methodology

The objective of this research was to see if using a larger data set influenced the team perception of the decision-making approach they were using. In study ten teams of five to six engineers were training in five decision-making techniques. The research was conducted in three phases. The first phase was to develop a test case and identify the trade study techniques that would be utilized. The second was to develop a methodology to test how decision makers in a team based problem solving situation perceived each of the trade study approaches with different sized data sets. The third phase was analysis of the data collected from the team decision makers.

2.1 Test Case Development and Trade Study Technique Selection

Trade studies are an application of MADM to a set of alternatives A_n according to a set of criteria C_m such that the performance of a given alternative A_i with respect to a particular criteria C_j is x_{ij}. The set of alternatives A_n can be defined as (1):

$$A = \{A_i, I = 1, 2, \ldots, n\} \tag{1}$$

The set of criteria C_m can be defined as (2):

$$C = \{C_m, m = 1, 2, \ldots, m\} \tag{2}$$

The total trade study of performance by criteria under examination can be represented as a matrix (Table 1).

Table 1: Formulation of a MADM Problem

	A_1	A_2	…	A_n
C_1	x_{11}	x_{12}	…	x_{1n}
C_2	X_{12}	x_{22}	…	x_{2n}
…	…	…	x_{ij}	…
C_m	X_{1m}	X_{2m}	…	X_{nm}

A vendor selection problem represents a common issue in supply chain management for both government and industry. A modified version of the problem originally presented to illustrate the use of the outranking technique ELECTRA [14] was used. In this problem five vendors, A_1 through A_5 were evaluated using two criteria sets

The data can be evaluated using a range of MADM approaches. The objective here is to select a tool that provides clarity in the decision-making approach. A good approach should provide sufficient insight and understanding so the decision maker can make an informed, sound decision. A range of different approaches were applied to the vendor selection evaluation dataset in order to illustrate how decision makers perceive alternative approaches. Five decision-making approaches were selected for this study:

Weighted Sum – This method is an elementary decision making tool that is the most commonly used approach for many systems engineering trade studies. In weighted sum, the score for an alternative A_i is determined by summing the products of the criteria weights k_i and the score for that alternative in relation to the criteria C_j given by x_{ij}. The advantage of this approach is that it is easy to apply and easy to explain to stakeholders. The assumption that all criteria can be evaluated independently is required for this approach. For further reading see Triantaphyllou & Baig [15].

Simple Multi-Attribute Rating Technique (SMART) – This method is an extension of weighted sum that allows the decision maker to use value functions to assess alternatives performance against specific criteria. The value functions can be tailored to meet specific decision maker needs so the functions are often non-linear. For further reading see Goodwin & Wright [16] and Oyetunji & Anderson [17].

Technique of Order Preference by Similarity to Ideal Solution (TOPIS) – This method assesses alternatives by computing their distances to two artificial alternatives; one which has the best level for all criteria considered and one which has the worst level for all criteria considered. TOPIS will select the alternative that has the closest distance to the ideal solution and the greatest distance from the worst case solution. For further reading see Tong, Wang, & Chen [18].

Analytical Hierarchy Process (AHP) - AHP is a quantitative comparison method that is based on pair-wise comparisons of decision criteria rather than utility and weighting functions. All individual criteria must be paired against all others and the results compiled in matrix form. The decision maker uses a numerical scale to compare the criteria and alternatives by pair-wise comparisons which will result in a final list of priorities. For further reading see Saaty & Salmanca-Buentello [19].

Outranking - This approach is fundamentally different from other decision making techniques in that a final ranking of alternative preferences is not reached. Outranking develops relationships between alternatives so that decision makers can determine if a given alternative A_i out performs (outranks) alternative A_j. An advantage of outranking is that is allows use of incomplete data sets. The emphasis is on understanding the performance of alternatives in relationship to each other rather than resulting in a final ranking. For more reading see Roy, Present, & Sithol [20].

2.2 Test Methodology

To see how decision makers perceive these trade study approaches a total of ten teams of five to six practicing engineers each were formed. Each team was trained in all trade study approaches, and then given one of the five approaches to use on the suppler selection problem and one of the two data sets to use for the analysis. . The first criteria set included items C1 through C4. The second criteria set included items C1 through C8. The criteria were defined as follows:

C1 - Subcontractor Size ($M) is a 3-year sales average; desirable vendor size is $950M.

C2 - Proximity (miles) is a pseudo criterion for to approximate the ability to support a Just In Time (JIT).
C3 - Cost per Unit ($) is the acquisition cost of a single item.
C4 - Experience is a qualitative assessment of the past experiences with the vendor.
C5 - ISO certification (yes/no).
C6 - Number of years of experience in the industry.
C7 - Size of our account with respect to the vendor's other accounts.
C8 - SAP compatible with our system.

The model used to form the teams is shown in Table 2.

Table 2: Model of Teams and Trade Study Approaches used in the Study

Trade Study Approach	Small Data Set	Large Data Set
Weighted Sum	Team 1	Team 6
SMART	Team 2	Team 7
TOPIS	Team 3	Team 8
AHP	Team 4	Team 9
Outranking	Team 5	Team 10

After completing their trade study each individual was given a survey (Table 3) to complete. Each five to six person team was given a data set and assigned one of the five decision making methods to evaluate potential suppliers and identify the top choice. Then each team member was asked to evaluate the decision-making method by responding to a set of six statements. For each statement the team members indicated the degree to which they agreed or disagreed using a 5 point Likert scale: {1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree}. Although the numbers on the Likert scale are not continuous, they are ordinal with a natural progression from a low value (strongly disagree) to a high value (strongly agree). For illustrative purposes, they have been analyzed with descriptive statistics as though they were continuous. Our dependent variables in this study were questions 1 through 5. Question 6 was included in the survey to gauge if prior familiarity with the tool influenced the survey results.

Table 3: Team Survey Questions.

1. After completing the training I am now comfortable using this technique.
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.
3. I am confident that the vendor recommendation using this technique is the best choice.
4. I could explain how this technique works to my coworker so they could use it.
5. I gained a better understanding of this problem by using this technique.
6. I was familiar with the trade study technique prior to taking this training.

2.3 Data Analysis Procedures

Teams were given 80 minute training sessions on each trade study approach. Then they were given a specific decision problem, data set and trade study approach to use to solve in another 80 minute session. Once completed the analysis each team member was given a 6 question survey to complete independently of the other team members. After all surveys were completed an open discussion was held with all the team members at once to discuss the survey results. Comments were collected during the discussion. The quantitative data collected was recorded and analyzed to show the mean, minimum, maximum, and standard deviations for each question for each team. The data was then summarized and comparisons between teams were done. Due to the limited sample size statistical analysis between the teams was not done. The open discussion with the teams were held to help clarify their responses to the surveys and to collect qualitative comments on their perceptions of the tools.

3. Results

The summary of results for all team members and all questions averaged across all five trade study approaches shows two questions with notable differences in responses (Table 4) between the small and large data sets. Question 3, "I am confident that the vendor recommendation using this technique is the best choice," and question 4, "I could explain how this technique works to my coworker so they could use it," both showed higher averages for team members who worked with the larger data sets. Of note also is that the level of familiarity with the tools appeared to be lower with the team members who worked with the larger data set. It is interesting that the average score for the teams who used the larger data set were slightly higher than the average score for the teams who used the smaller data set (+0.13) even though the familiarity was lower (-0.27).

Table 4: Summary of Team Member Responses for all Decision-Making Approaches

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	3.20	3.14
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	3.68	3.65
3. I am confident that the vendor recommendation using this technique is the best choice.	3.80	4.32
4. I could explain how this technique works to my coworker so they could use it.	3.68	3.92
5. I gained a better understanding of this problem by using this technique.	3.88	3.89
6. I was familiar with the trade study technique prior to taking this training.	2.64	2.37
Average (questions 1 – 5 only)	3.65	3.78

This level of analysis provides only minimal insight since the averages are across multiple teams (and multiple decision making approaches). A better understanding of the influence that the different size data sets had on the team members is shown by looking at the individual trade study approaches.

3.1 Weighted Sum

The Weighted Sum technique received generally high ratings when applied to both the small and large data sets (Table 5) with the average score for the large data set team member responses was 0.21 lower than the average score for the small data set team member responses. Familiarity scores were similar for both teams... The scores for the team using the large data set were all slightly lower. Familiarity with the tool was similar for both teams. A common theme in the discussions with both teams was the ease of use and the relative ease they had in explaining the technique to a stakeholder who was not directly involved in the analysis process. This was noted as one of the most desirable aspects of this approach. Also of interest was the relatively weak score for question 5, "I gained a better understanding of this problem by using this technique." It appears that the approach is easy to understand but does not help the decision maker develop a better understanding of the problem as the other approaches in this study.

Table 5: Team Responses for the Weighted Sum Approach

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	4.20	4.00
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	4.40	4.17
3. I am confident that the vendor recommendation using this technique is the best choice.	4.80	4.67
4. I could explain how this technique works to my coworker so they could use it.	4.80	4.50
5. I gained a better understanding of this problem by using this technique.	3.20	3.00
6. I was familiar with the trade study technique prior to taking this training.	2.80	2.83
Average (questions 1 – 5 only)	4.28	4.07

3.2 SMART

The SMART technique also received generally high ratings indicating primarily agreement with the questions across the different team members (Table 6), although the average score for the large data set team member responses was

0.36 lower than the average score for the small data set team member responses. The team using the larger data set was less familiar with SMART beginning the study. The most notable difference between the weighted sum and SMART was the lower level of familiarity with the SMART tool. SMART, as a tool is more complicated than Weighted Sum. Although this approach is viewed as more complicated than Weighted Sum both teams had high average scores on question 4, "I could explain how this technique works to my coworkers so they could use it." Discussions with team members showed that the graphical presentation of the results with cost plotted against the total performance on the other criteria encouraged discussion of results thereby making the results easier to understand for the stakeholders. SMART does not report the best alternative, but the presentation encourages discussion as to the relative benefits and costs of each alternatives. Inferior alternatives are also easy to discard.

Table 6: Team Responses for the SMART Approach

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	3.40	3.20
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	4.40	4.20
3. I am confident that the vendor recommendation using this technique is the best choice.	4.80	4.20
4. I could explain how this technique works to my coworker so they could use it.	5.00	4.40
5. I gained a better understanding of this problem by using this technique.	4.20	4.00
6. I was familiar with the trade study technique prior to taking this training.	2.40	2.20
Average (questions 1 – 5 only)	4.36	4.00

3.3 TOPIS

The TOPIS technique received slightly lower ratings than weighted sum and SMART. The average score for both teams was 4.00. The team using the larger data set had a much lower level of familiarity with the tool prior to the training (-0.77) than the team using the smaller data set. TOPIS was seen by the participants as a more involved approach that typically involved more work but did provide a better understanding into the problem than weighted sum and SMART. Team members did note that in this particular problem, selecting a supplier, TOPIS might not be the best approach because none of the alternatives had one criteria that would be viewed as critical to the selection. A problem where one criterion, such as safety, could cancel good performance in all other criteria was seen as a better application for this approach.

Table 7: Team Responses for the TOPIS Approach

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	3.40	3.17
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	4.00	3.83
3. I am confident that the vendor recommendation using this technique is the best choice.	4.20	4.50
4. I could explain how this technique works to my coworker so they could use it.	4.00	4.00
5. I gained a better understanding of this problem by using this technique.	4.40	4.50
6. I was familiar with the trade study technique prior to taking this training.	2.60	1.83
Average (questions 1 – 5 only)	4.00	4.00

3.4 AHP

The AHP, which is cognitively more complex that weighted sum and SMART, reversed the trend of having average scores for team members lower when using the larger data set (Table 8). The average score for the large data set team member responses was .72 higher than the average score for the small data set team member responses. Scores for all the individual questions were higher. Part of this large difference may be attributed to a slightly higher level of familiarity with the tool for the team that was using the larger data set. Both teams used almost the allotted 80 minutes to complete the task; however, the team members noted they did not feel rushed. Overall scores for AHP were lower than the other techniques. This may also be influenced by the time constraint the team was operating under. It is also possible that the dynamics for this team were different than for other teams. Participants from both teams noted the pair-wise comparisons became tedious. Scores for question 5, "I gained a better understanding of this problem by using this approach," increased by 0.60 with the larger data set.

Table 8: Team Responses for the AHP Approach

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	2.60	3.00
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	3.00	3.20
3. I am confident that the vendor recommendation using this technique is the best choice.	3.00	4.40
4. I could explain how this technique works to my coworker so they could use it.	2.20	3.20
5. I gained a better understanding of this problem by using this technique.	3.20	3.80
6. I was familiar with the trade study technique prior to taking this training.	2.60	3.00
Average (questions 1 – 5 only)	2.80	3.52

3.5 Outranking

The Outranking, which was the most cognitively complex, received generally lower scores than the other techniques (Table 9). Scores did follow the same pattern as the other complex approach, AHP. The average score for the large data set team member responses was .53 higher than the average score for the small data set team member responses. The average team familiarity that was proposed as a possible explanation for the score reversals when this was observed with AHP is not evident here. Familiarity with the tool was low for both teams and familiarity for the team using the larger data set was well below that reported for the team using the small data set. The discussion with both teams showed that they were still not comfortable with the approach after completing the analysis as shown in their responses to question 1, "After completing the training I am now comfortable using this technique." Of interest is that generally scores are higher for the remaining questions 2 through 5 for the team using the larger data set. Members of both teams' noted that Outranking was able to demonstrate that alternatives can outperform each other in different criteria making a clear ranking of alternatives seem less representative of the true nature of the problem. Both teams used the full 80 minutes to complete the task.

Table 9: Team Responses for the Outranking Technique

Survey Question	Small Data Set	Large Data Set
1. After completing the training I am now comfortable using this technique.	2.40	2.33
2. After using this tool on the vendor selection problem I would be comfortable using this tool on work related problems.	2.60	2.83
3. I am confident that the vendor recommendation using this technique is the best choice.	2.20	3.83
4. I could explain how this technique works to my coworker so they could use it.	2.40	3.50
5. I gained a better understanding of this problem by using this technique.	4.40	4.17
6. I was familiar with the trade study technique prior to taking this training.	2.80	2.00
Average (questions 1 – 5 only)	2.80	3.33

4. Comparison of Approaches

In the initial study dealing with only the small data set the quantitative and qualitative results indicated a possible tradeoff between comfort with the approach and understanding of the problem. Also, the results indicated that the cognitively simple techniques, weighted sum and SMART, were preferred over the more complex approaches. In the second study the large data set was added. Now, the cognitively more complex techniques, AHP and outranking had generally higher scores. The teams using AHP and outranking both noted they used all the allotted; however, even under the time limitation scores were higher. Also of interest was that the scores for explaining how this technique works to my coworkers who showed a marked decrease as the tool complexity increased among teams using the small data sets but this trend was reversed among teams using the large data set. The data appears to support the general premise that tool selection should consider the data set to be studied.

5. Conclusions

These two studies attempted to address this issue of how does the decision-making approach used by an engineering team influence their confidence with their decision and does the amount of data in the problem change that confidence. The first study showed that approach complexity, user comfort with the approach, explaining to coworkers and understanding of the problem may all be related to the trade study approach used. The second study showed that the size of the data set to be analyzed does appear to also influence how the trade study tool used will be viewed.

It was previously noted that system engineers often become familiar with a single trade study approach and may tend to use it to address a range of decisions. These studies did indicate that while team members' comfortable level with the tool does appear to be related to its complexity level, the size of the data set used in the study will also influence which tool should be considered.

Although the data for this study is limited, there are several extensions that are under consideration. The relationship between a team members' prior knowledge of the tool and their subsequent use in this new study is an important next step in this research. Also, even with the small team size of five to six members they may be work to see how the variation in team member experience with the tools influence their results. This work did a cursory review of team member demographics, such as education and work history, did not show an impact on the result; however, this may be influenced by the relatively small size of this study. One significant extension is to determine when the team has arrived at the correct answer. This can be more challenging since decision analysis tools are often concerned with fully exploring the data set and reaching consensus among the decision makers rather than arriving at an optimal solution. When the common practice of using distributed teams is added then these questions become more critical because of the limitations in team member interactions.

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